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Achieving Low Carbon Emission for Dynamically Charging Electric Vehicles through Renewable Energy Integration

XIAOLIN MOU[1] (Member, IEEE), YINGJI ZHANG[2], JING JIANG[3] (Member, IEEE), and HONGJIAN SUN[2] (Senior Member, IEEE)

[1]Department of Electronic and Electrical Engineering, University of Sheffield, Sheffield, S1 4DE, UK

[2]Department of Engineering, Durham University, Durham, DH1 3LE, UK

[3]Department of Mathematics, Physics and Electrical Engineering, University of Northumbria, Newcastle, NE1 8ST, UK

Corresponding author: Hongjian Sun (e-mail: hongjian.sun@durham.ac.uk).

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ABSTRACT Dynamic wireless charging for Electric Vehicles (EVs) can promote the take-up of EVs due to its potential of extending the driving range and reducing the size and cost of batteries of EVs. However, its dynamic charging demand and rigorous operation requirements may stress the power grid and increase carbon emissions. A novel adaptive dynamic wireless charging system is proposed that enables mobile EVs to be powered by renewable wind energy by taking advantages of our proposed traffic flow-based charging demand prediction programme. The aim is to cut down the system cost and carbon emissions at the same time, whilst realising fast demand prediction and supply response as well as relieving the peak demand on the power grid. Simulation results show that the proposed system can adaptively adjust the demand side energy response according to customers' welfare analysis and charging price, thereby to determine the power supply method. Moreover, due to the prioritised use of renewable energy, EV charging system requires less electricity from the power grid and thus the overall carbon emissions are reduced by 63.7%.

INDEX TERMS Dynamic wireless charging, electric vehicles, renewable energy, and demand response.

Nomenclature

χ_i	The amount of electricity consumed by consumer i (i^{th} EV) in the Charging Zone, kWh
ω_i	The willingness to pay parameter of consumer i (i^{th} EV)
i	Serial number of EVs in charging demand, $i \in [0, N]$
j	Number of EVs responding for charging, $j \in [0, N]$
M	Number of pads that wind energy can charge
M_p	Predicted number of pads by charging demand prediction (before Demand Response)
M_r	Real number of pads after Demand Response and auto selection
N	Traffic flow
n	Maximum number of pads that wind energy can charge
N_{max}	The maximum traffic flow in a specified time period
p	Charging price, $£/kWh$
p_1	The lowest charging price when wind energy is adequate to supply all predicted demand (M_p), $£/kWh$
p_2	The medium charging price when wind energy can supply parts of the predicted demand and the Grid compensates for the supply deficit, $£/kWh$
p_3	The highest charging price when no wind energy is available and the grid supply all charging demand, $£/kWh$
P_g	The amount of power from the grid, kW
P_m	Maximum wind power of the system, kW
P_o	Nominal charging power per charging pad, kW
P_r	Total demand power after Demand Response, kW
P_{wt}	The wind power of all wind turbines, kW
$s_{M_r[or M]}$	The serial number of pads to be turned on
$U_i(\chi_i, \omega_i)$	The utility function of consumer i (i^{th} EV)
V	Wind speed, m/s
$W_i(\chi_i, \omega_i)$	The welfare function of consumer i (i^{th} EV)

I. INTRODUCTION

Renewable energy generation and Electric Vehicles (EVs) have been widely used in recent decades due to the pressing concerns about climate change, air pollution, and energy security [1]. Global sales of new EVs passed a million units, according to McKinsey's Electric Vehicle Index [2]. Under the current growth trajectory, EV producers could almost quadruple that achievement by 2020, moving to 4.5 million units that are 5% of the overall global light-vehicle market. The main obstacles for larger take-up of EVs, from the consumers' perspective, are the limited driving range, long charging time, lack of convenient charging infrastructure and relatively high purchase price compared with conventional internal combustion engine vehicles (ICEVs) [3]. On the other hand, governments also have concerns about the potential increase in the electricity consumption and carbon emissions due to EVs charging, especially during peak demand periods, even though many of them have launched preferential purchase policies to advocate EVs. To tackle these problems, possible solutions have been proposed and inspected, such as advancement of battery technologies and materials, battery replacement, wireless charging, integration of renewable energy sources (RESs), and demand-side management (DSM) [4].

Wireless EVs charging technology can be divided into static wireless EVs charging and dynamic wireless EVs charging. C. Panchal et al. proposed a review of static and dynamic wireless EVs charging system [5]. This paper will focus on the dynamic wireless charging technology. Dynamic wireless charging for EVs stands for the technologies transferring power wirelessly to EVs when they are moving on the "road" - the dedicated charging lane [6]. Theoretically, the driving range of EVs can reach infinite as long as EVs have consistent access to the charging lanes and the charging power rating meets the requirement of EVs. This would dramatically help reduce the size and cost of batteries, which remain drawbacks of the static EV charging [7] as well as the main reason for holding back potential customers from purchasing EVs. Ideally, dynamic wireless EVs charging can achieve near zero carbon emission if the power is entirely supplied by RESs such as wind and solar energy. M. Longo [8] provides the feasibility of significantly reducing global greenhouse gas emissions by integrating EVs with RESs for sustainable mobility. The paper presents some idea descriptions such as EV integration with RESs, EV coordination, and electrical network integration with the management of distribution grid, etc. However, the simulation analysis in this manuscript is only based on solar photovoltaic.

The first implementation of the dynamic wireless power transfer system in EVs charging was performed at Lawrence Berkeley National Laboratory in 1976 [9]. Then, the dynamic wireless charging apparatus for EVs was invented by Maurice Hutin and Maurice Leblanc in 1894 [10]. One leading research group is the Korea Advanced Institute of Science and Technology (KAIST) whose On-line Electric Vehicle (OLEV) appears to be the most market readiness. Launched in 2009, the OLEV has undergone six generations of development by applying Magnetic Resonant Coupling WPT (MRCWPT) technology [4], [11], [12]. Oak Ridge National Laboratory (ORNL) started their investigation in the inductive dynamic wireless charging in 2011. They are the first group that found the circular coil topology can obtain smaller lateral tolerance while capacitor regulation at both supply and receiving sides can effectively smooth power pulsation [13]–[16]. Bombardier research team provided wireless charging solutions for both trams and buses with their patented PRIMOVE energy pick-up systems in both static and dynamic scenarios. Demonstration trials were successfully performed in Germany, Belgium, and China [17]–[19].

Although dynamic wireless charging prototypes for EVs have been continuously developed and improved to achieve higher efficiency and lower costs, the existing commercial operations are only realised on public electric buses and trams at low speeds in urban area [4], [17], [20]. One major obstacle is the difficulty in precisely predicting and quickly responding to the charging demands of EVs, particularly the private EVs, in the dynamic wireless charging systems. Unlike the controllable public electric buses that have fixed routes and almost fixed speeds due to the predetermined schedules, the driving behaviour of private EVs is unpredictable as it is influenced by many factors, such as personal habits, traffic conditions, climate, and contingencies. In addition, the electricity pricing is one research topic in EVs charging system. J. Zethmayr [21] proposes an analysis of hourly electricity pricing for EVs, which is based on three representative EVs and four daily driving amounts level. The comparison results show that using the price signal to manage charging is almost certainly one of the best (cheapest) strategies. Moreover, by motivating EV owners to charge their vehicles when power supply exceeds demand, dynamic pricing can improve system load shape and capacity utilization, reduce consumer costs, and cut pollution. However, the pricing method does not be mentioned in this paper.

Dynamic wireless EV charging system can be classified into the long-track type and individual-transmitter type. The long-track type has advantages of simple structure and low cost, however, the efficiency of the long-track type structure is low. The individual-transmitter type has high efficiency and the individual transmitter can be turned off when the EV leaves [22]. There are many power supply designs of individual-transmitter type in pre literature. S. Zhou et al. [22] proposed a cost-reducing multiplexing LCC module to save 75% the costs of compensation network compared to normal LCC type dynamic wireless EV charging. C. Cai et al. proposed an LCL-S/LCL switching topology in dynamic wireless EV charging system which is simplified to achieve constant current in the transmitting coil and load-independent constant current. Moreover, this design is easy to control [23]. A double-coil excitation method with the crossed-DD coil structure was proposed by L. Xiang et al., which specifically concentrated on the feature of dynamic mutual inductance [24].

In dynamic wireless EV charging system, the misalignment between transmitter coil and receiver coil is going to happen. S. Wang et al. provided an optimisation design for series-series dynamic WPT system to improve the transfer efficiency when the misalignment happens [25]. One big challenge in dynamic wireless EV charging system is the output power pulsation. Yijie.Wang et al. presented the DDQ type of the receiver coil and double-side LCC topology can optimize the system design to solve the output power pulsation problem [26]. Q. Zhu et al. proposed a decoupling-characteristic-based segmental switching strategy to minimising the output pulsation [27]. Route optimization of dynamic wireless EV charging is another hot topic which includes communication technology and Internet of Things (IoT) [28] [29].

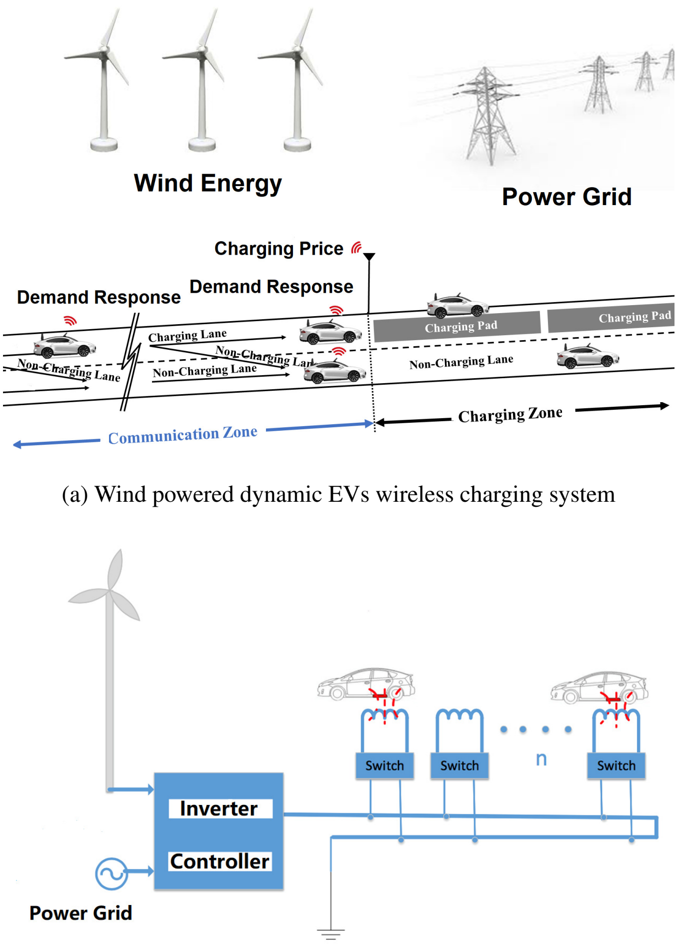
Another obstacle is the stricter operation requirements of dynamic wireless charging for EVs. Unlike the plug-in (wired) charging and static wireless charging which could last for a few hours, dynamic wireless charging shall be done within only a few seconds and up to few minutes depending on several factors including the driving speed, charging lane configuration, and charging schedule [6]. Thus, dynamic wireless charging requires much higher charging power and faster balancing response from the charging system and power supply system [6], [7], [30]. Unfortunately, the existing dynamic wireless EV charging prototypes are limited to fixed and slow driving speeds. In addition, as more dynamic wireless EV charging systems are installed and connected to the power grid, this could pose a great strain on the power grid, in particular during the peak demand time. Situations may even be worse if fossil fuels are still used as the dominating energy sources, as this could lead to significant amount of carbon emissions.

Considering the above design challenges, this paper proposes an adaptive renewable (wind) energy-powered dynamic wireless charging system for EVs. The calculation of wind power of a turbine is based on wind speed. The real-time wind speed data can be provided from weather observatories or using the predicted wind speeds methods like regression technique and moving-average process (ARMA) [31]. Christiaan et al. presented a comparison of regression algorithms for wind speed forecasting [32]. In this paper, we used real-time wind speed data to do simulation. The objectives of this system are: 1). to maximise the utilisation of renewable wind energy whilst mitigating the uncertainties caused by intermittent renewable energy and demand variation; 2). to reduce the carbon emissions (ideally achieving zero carbon emission) caused by the EVs charging system, which typically uses electricity generated by generation mix (coal, gas etc.); and 3). to improve the range of EVs (ideally infinity range) by using dynamic and wireless EV charging infrastructure.

The novelties of this work are summarised as follows:

- An adaptive dynamic wireless EVs charging system is proposed that uses electricity from both wind energy and power grid to meet charging demand. The use of RESs (wind energy) is prioritised to reduce the peak demand pressure on the power grid and its carbon emissions. A complete simulation system is proposed in this paper. The power supply source can be adaptively chosen according to the weather (wind speed) and traffic condition prediction.
- A special charging lane design which can turn on the selected charging pad. Unlike existing research that limits the vehicle driving speed to a fixed low value for ensuring the sufficient charging time, this proposed system only needs EVs to slow down a bit when they pass through the opened charging pads. On other sections of the charging lane, EVs can be driven at any speed that satisfies national speed limit.
- Adjust charging demand through different electricity price: a three-level pricing scheme which is according to the wind energy and traffic flow is proposed to incentivise EVs charging demand response to avoid peak time charging.

The rest of the paper is organised as follows: Section II



(a) Wind powered dynamic EVs wireless charging system

(b) Schematic diagram of charging system

FIGURE 1: Renewable wind energy powered dynamic EVs wireless charging system.

presents the structure and principles of the adaptive dynamic wireless charging system. The case study of a UK motorway and simulation results are discussed in Section III and Section IV, respectively. Finally, conclusions are drawn in Section V.

II. WIND-POWERED DYNAMIC WIRELESS EVs CHARGING SYSTEM OVERVIEW

The proposed dynamic wireless EVs charging system can be directly powered by renewable energy, particularly wind energy. Meanwhile, it can be powered by the utility power grid if renewable energy is insufficient. Theodoros V et al. proposed simulation results which showed wind speed can influence the supply and demand balance. e.g. High wind variation requires higher charging increase rates or the integration of energy storage system to minimize supply variance. Otherwise, small wind fluctuation needs to planning of RESs integration within the charging infrastructure according to traffic patterns [33]. So we proposed this system can apply to any wind speed and maximize the use of wind energy.

Fig. 1 shows a diagram of the system. The aim of our design is an adaptive charging system which can promote the use of renewable wind energy. Energy storage places close to the charging lane system can be a good option not to overload the grid. This can be charged when there is excess production by wind and discharged in no-wind periods and in this way help the system as well. However, to simplify the overall system model and the cost, energy storage has not been considered in our current design, and we left it as future research. The EV charging demand is predicted using the traffic flow data and traffic condition classification methods. Both wind energy and the power grid provide electricity to the EV charging system but wind energy is the prioritised supply source, hence the electricity will be imported from the power grid only when wind energy is inadequate to meet all charging demands. The charging lane adopts the multiple segmented transmitters rail design due to its higher power transfer efficiency in comparison with long transmitter rail configuration [34] (The segmented transmitter will be referred to as the charging pad or pad in later parts of this paper). Each charging pad is controlled by a switch that can be turned on/off via the automatic selection module.

Fig. 2 describes the key components and operation principles of the adaptive dynamic wireless charging system for EVs driving on highways. The system consists of four parts: wind energy prediction module, charging demand prediction module, demand response optimisation module, and automatic selection module. The details of operating the whole system are as follows:

Wind energy prediction module:

1) Initialise the maximum power (P_m) that is the sum of rated power of all wind turbines, and then calculate the maximum number of pads that P_m can supply, i.e. n.
2) Forecast future (time scale depending on system design) wind energy (P_{wt}) via wind speed (V_t) prediction which can be obtained from the historical wind data and wind speed prediction algorithm, such as Auto Regression Algorithm.
3) Decide the number of pads that P_{wt} can supply, i.e., $M = \lfloor (P_{wt}/P_m) * n \rfloor$.

Charging demand prediction module:

4) Forecast future (time scale depending on system design) traffic flow using traffic flow counting infrastructure.
5) Decide the desired number of pads (M_p) according to the traffic phase classification and charging demand prediction programme.

Demand Response Module:

6) Decide the charging price (p) based on the values of M and M_p, and then communicate p to potential consumers in the communication zone in order to operate price-incentivised Demand Response and collect the total demand power (P_r) and calculate the number of pads (M_r) required to supply these charging demand. $M_r = \lceil (P_r/100) \rceil$, here assume the charging power of each pad is 100.

Automatic selection module:

7) Decide the appropriate number of pads to be switched on by comparing demand and supply powers, i.e. P_r and P_{wt}. At this stage, P_{wt} is fully used aiming at maximising the utilisation of wind energy.
8) Decide the energy supply source, i.e., pure wind energy, or wind energy plus energy from the power grid.

There are two supply modes that system can choose:

- Mode 1: if $M \geq M_r$, switch on M pads. This means wind energy can sufficiently meet all charging demands and all available wind energy is used up.
- Mode 2: if $M < M_r$, switch on M_r pads. This means wind energy is insufficient to supply all charging demands, so M pads are charged by wind energy, and the remaining ($M_r - M$) pads are charged by the power grid, consuming ($P_r - P_{wt}$) kW electricity.

A. WIND ENERGY PREDICATION MODULE

The power of wind turbines can be given by [35]:

$$P = (1/2)\rho A V^3 C_p \tag{1}$$

where P is the power of the wind turbine, C_p is the power coefficient, A is swept area of the turbine, ρ is air density, V is actual wind speed below the maximum wind speed limit.

Taking all characteristics of mechanical, electrical and material into account, the overall wind power output of a turbine with respect to the wind speed is represented in the

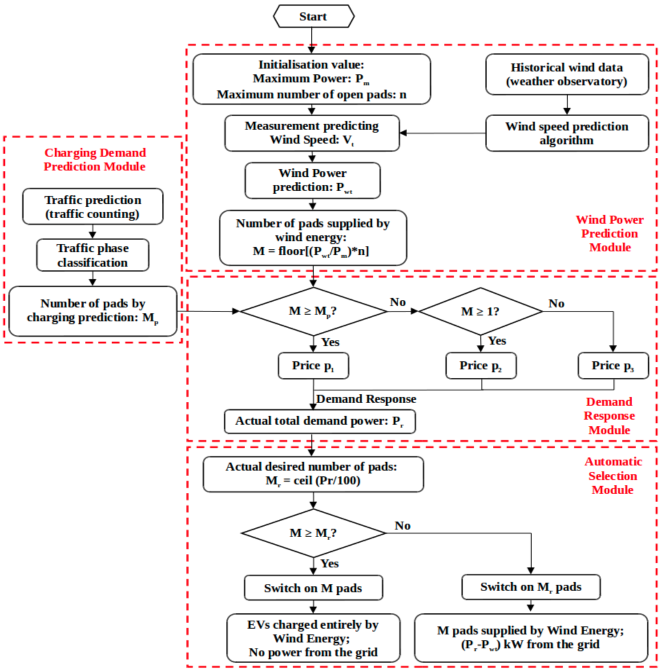


FIGURE 2: System function flowchart

form of the dynamic power curve provided by the turbine manufactures. The common dynamic power curve can be formulated by [36]:

$$P_{wt0} = \begin{cases} 0, & V < V_{cut-in} \\ f(V), & V_{cut-in} \leq V < V_{rated} \\ P_{rated}, & V_{rated} \leq V < V_{cut-out} \end{cases} \tag{2}$$

where P_{wt0} is the actual power output of a turbine corresponding to a specific wind speed, $f(V)$ is a function of wind speed, P_{rated} is the rated power of a specific wind turbine representing the maximum power that a turbine can generate, V_{cut-in} is the cut-in wind speed specified by the turbine below which the wind turbine cannot generate electricity, V_{rated} is the rated wind speed above which the wind turbine power output remains at the rated power and $V_{cut-out}$ is the cut-out wind speed above which the turbine will stall. The power conditions corresponding to the wind speeds above the cut-out wind speed are complicated and out of the scope of this paper.

If a certain number of wind turbines are used together, the total power output is the sum of the power generated by all turbines. We assume the total rated power of all turbines is equivalent to the power demand of the maximum number of charging pads calculated by the charging demand prediction programme, i.e. n pads can be supplied completely by wind energy when all wind turbines operate in their rated conditions. For easy operation, the same type of wind turbines are used in our system and the wake effect among turbines are not considered. Then, the number of turbines needed can be calculated by:

$$m = \frac{P_o \times n}{P_{rated}} \tag{3}$$

where m is the required number of wind turbines, P_o is the nominal charging power of each pad and P_{rated} is the rated power of individual turbine. As a result, the total actual wind power output of the system and the total rated power output of all turbines can be obtained by:

$$P_{wt} = m \times P_{wt0} \tag{4}$$

$$P_m = m \times P_{rated} \tag{5}$$

where P_{wt} is the total actual wind power output of all turbines at wind speed V_t and P_m is the total rated power output of all turbines.

Since the wind power varies with wind speed, the actual number of charging pads (M) that can be powered by wind energy is calculated by:

$$M = \lfloor \frac{P_{wt}}{P_o} \rfloor = \lfloor \frac{n \times P_{wt}}{m \times P_{rated}} \rfloor = \lfloor n \frac{P_{wt}}{P_m} \rfloor \tag{6}$$

where P_{wt} is the total actual wind power output of all turbines at wind speed V and P_m is the total rated power output of all turbines.

B. CHARGING DEMAND PREDICATION MODULE

Since traffic flow reflects the potential charging demand to some extent, particularly when the entire vehicle fleet is EVs in the future, it can be used as an easy demand prediction approach. This could make better use of the existing traffic flow counting infrastructure and improve the efficiency and accuracy of charging demand prediction.

According to [37], traffic conditions are commonly classified into two, three or five phases: congested/ non-congested (two phases), congested/ medium congested/ non-congested (three phases) and free flow/ non-congested/ lightly congested/ congested/ heavily congested (five phases). Hence, charging demand prediction programmes can be proposed based on these traffic condition classifications. In the multiple segmented transmitters rail configuration, the corresponding desired number of charging pads by demand prediction can then be determined in a controlled manner. For example, Table 1 shows a five-phase charging demand prediction programme which will be applied in the case study in Section III.

In the programme, N is the traffic flow, M_p is the predicted desired number of charging pads by charging demand prediction programme, N_{max} is the maximum traffic flow in a specified time period and a_1, a_2, a_3 and a_4 are the upper limits of traffic flow at each phase. N_{max}, a_1, a_2, a_3 and a_4 can be defined by analysing historical traffic data or traffic flow forecasting and they may vary with places, climate and regulations etc. For the former four phases, the values of M_p are obtained by multiplying the upper limit of traffic flow of

Traffic flow, N	Traffic phase	Desired number of charging pads, M_p
$N \leq a_1$	Free flow	$1.2a_1$
$a_1 < N \leq a_2$	No-congested	$1.2a_2$
$a_2 < N \leq a_3$	Lightly congested	$1.2a_3$
$a_3 < N \leq a_4$	Congested	$1.2a_4$
$N > a_4$	Heavily congested	$1.2N_{max}$

TABLE 1: Five-phase charging demand prediction program

that phase by a safety factor of 1.2. (Here, the safety factor is a random value between 1 to 1.3. The aim of using the safety factor is to ensure that the number of charging pads is greater than the traffic flow requirements. A safety factor of 1 means that a design can just meet the design load, and cannot support any additional load. A design with safety factor < 1 are not viable; 1 is the minimum value [38].) while for the last phase, the value of M_p, i.e. the maximum number of pads required to be switched on by demand prediction (notated as $'s'$), is obtained by multiplying the maximum traffic flow N_{max} by a safety factor of 1.2. In practical operation, M_p shall be rounded-ceiling to integers.

C. DEMAND RESPONSE OPTIMISATION MODULE

The electricity demand curve reflects that demand declines with the price rise, so price-based Demand Response (DR) techniques are commonly used in solving DR optimisation problems. There are existing researches about flat pricing [3], peak load pricing [39] and adaptive pricing (real-time) [4], [6] for household DR and static EV charging DR. Unfortunately, these DR algorithms do not suit the highway traffic conditions such as fast speed, short charging duration, and dynamic entry and leaving.

In the dynamic wireless EV charging system, the time of EV passes through a single charging pad is around 1 second at the most, e.g. in our case, the EV speed is 70 mph and 1 meter charging pad is 0.3 second. However, the latency of demand response in smart grid communication network is 2 second [40]. So the response time of general DR strategy cannot adjust wireless dynamic EVs charging. In our system, a three-layer pricing scheme is formulated as (7), aiming at encouraging more charging demand when wind energy is sufficient while reducing charging demand when wind energy is insufficient.

$$p = \begin{cases} p_1, & M \geq M_p \\ p_2, & 1 \leq M < M_p \\ p_3, & M = 0 \end{cases} \tag{7}$$

where p is the charging price sending to customers, p_1 is the lowest price when wind energy is adequate to supply all predicted demand, p_2 is the medium price when wind energy can supply parts of the predicted demand and the grid compensates for the supply deficit and p_3 is the highest price when no wind energy is available and the grid is required to supply all charging demand. Therefore, $p_1 < p_2 < p_3$.

The charging price will be communicated to potential consumers when they enter the communication zone. The response of consumer i to the charging price is modelled by carefully selected Utility Function [41]:

$$U_i(\chi_i, \omega_i) = \omega_i \log \chi_i, i = 1, 2, .., N \tag{8}$$

where $U_i(\chi_i, \omega_i)$ is the utility function of consumer i, χ_i is the amount of electricity used by consumer i and ω_i is the willingness to pay parameter which varies between different customers. We assume ω_i is a random integer ranging between 1 and N.

The welfare of consumer i would then become:

$$W_i(\chi_i, \omega_i) = U_i(\chi_i, \omega_i) - p\chi_i \tag{9}$$

Assuming all consumers maximize their own welfare, the optimisation problem at the consumer side is presented as:

$$\begin{aligned} \text{max} \quad & \sum_{i=1}^{N} W_i(\chi_i, \omega_i) \\ \text{subject to} \quad & \chi_i \geq 0 \end{aligned} \tag{10}$$

The solution to the optimisation problem is obtained by solving equation (11):

$$\frac{\partial W_i(\chi_i, \omega_i)}{\partial \chi_i} = 0 \tag{11}$$

i.e. the optimal amount of electricity consumption for the maximum welfare of consumer i is:

$$\chi_i = \frac{\omega_i}{p \times (\ln 10)} \tag{12}$$

Once the optimal amount of electricity of all potential consumers is obtained, the welfare of each potential customer at the given charging price will then be calculated. It is assumed that only customers with positive maximum welfare, i.e.,$W_i(\chi_i, \omega_i) \geq 0$ will accept the charging price and get charged in the charging zone.

Among all available commercial EVs, the required charging power varies dramatically, ranging from 60-80 kW (low power, such as Smart, Volkswagen, and Nissan) to 266-581 kW (high power, such as Tesla, Volvo and BMW) [42].

In the current system, we consider low-power EVs because the Europe Best Selling Pure EVs in 2018 is Volkswagen e-golf (power rang below 100 kW) [43]. If the required EV is a higher power EV which higher than 100 kW, in this system cannot provide energy and send a rejection notice to the driver in the communication zone. However, we can improve the charging power of each pad to a higher value to suit for high power EVs.

In order to simplified calculation, assuming the number of EVs responding for charging is $j(j \in [0, N])$, and the required power of the batteries on these EVs are modelled as random integers equal to 100 kW (the actual required power of battery may be an arbitrary value between 0-100 kW). In practical, using the SOC of EVs battery as required power to calculate the total demand power can get the exact value. Hence, the total demand power becomes:

$$P_r = \sum_{k=1}^{j} 100 \times rand(1)_k \tag{13}$$

where P_r is the total demand power and k is the serial number of EVs responding for charging.

D. AUTOMATIC SELECTION MODULE

In the automatic selection module, the corresponding number of pads for providing those demand power is first calculated:

$$M_r = \lceil \frac{P_r}{P_o} \rceil \tag{14}$$

where M_r is the number of pads for providing P_r demand power and P_o is the nominal power of each pad.

By comparing the value of supply power and demand power, i.e. P_{wt} and P_r, the final number of pads to be turned on and the supply source(s) are determined aiming at maximising the utilisation of wind energy as well as minimising the interference to the grid. At this stage, the system performs in two cases as follows.

- Case 1: $P_{wt} \geq P_r$, switching on M pads. This means wind energy can independently meet all charging demand so all wind energy is used to encourage customers to charge and eliminate interference to the grid due to wind energy surplus. Denoting the amount of power imported from the gird as P_g. Because of in this case, the energy supply from power grid is zero, so $P_g = 0$.
- Case 2: $P_{wt} < P_r$, switching on M_r pads. This means wind energy can not meet all charging demand and the grid is required to compensate the power deficit. The amount of compensation power from the grid is calculated as:
$$P_g = P_r - P_{wt} \tag{15}$$

III. CASE STUDY

In this section, a case study of the adaptive dynamic wireless charging system on a British Motorway is demonstrated and the simulation results of different traffic and wind scenarios are discussed. As shown in Fig. 1a, traffic lane is a dual-lane: one is charging lane and the other is non-charging lane. Communication requirements between the system and the EVs are necessary before the EV enters the charging lane. The EVs receive price from the system and the system will decide whether to charge the EVs. The communication zone is set to 5 km and operation interval is three minutes, i.e. $T = 3$ min.

A. TRAFFIC FLOW

MIDAS Site 9203 (LM4) on British Motorway A1 (M) was selected as the sample charging lane. The charging lane is 1 km long and the traffic flow counting infrastructure locates at the entry point of this lane. The historical traffic flow data in 2014 was obtained from [44], which showed that the double-lane three-minute traffic flow fluctuated between 2 and 71 vehicles. It was also noted that there existed different traffic patterns between weekdays and weekends as displayed in Fig. 3. The average three-minute traffic flow of Mondays to Fridays is generally higher than that of Saturdays and Sundays. In addition, there are two distinguishing traffic flow peaks during weekdays, one around 40 vehicles from 7 am to 9 am and the other between 50 and 62 vehicles from 4 pm to 6 pm. However, no significant peak occurs at weekends and the highest traffic flow reaches only 30 to 40 vehicles between 11 am and 5 pm.

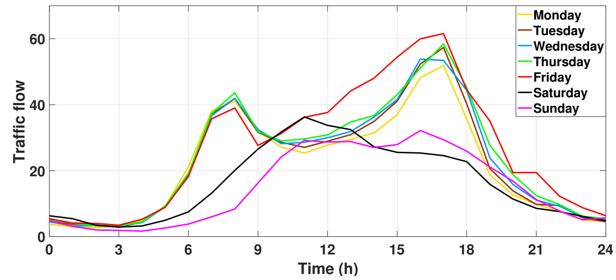


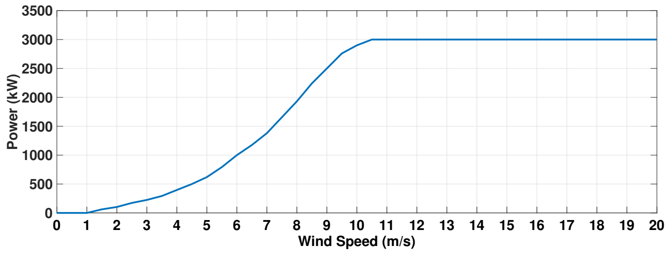
FIGURE 3: 24-hour traffic flow data

On the other hand, it was found that there was no significant correlation between traffic flow and the driving speed. For instance, for driving speed at 110 km/h (68 mph), the three-minute traffic flow ranged from 2 vehicles to 63 vehicles and the speed could occur at any time of a day. In majority intervals, the driving speed was relatively stable between 103 km/h (64 mph) and 120 km/h (75 mph), which complied with the speed limit of British Motorways at 112 km/h (70 mph) [45]. In addition, [46] proved that the driving speeds had no impact on the power transfer efficiency of multiple segmented dynamic charging systems. Therefore, it is reasonable for our adaptive dynamic wireless charging system to operate based on the traffic flow rather than the driving speed.

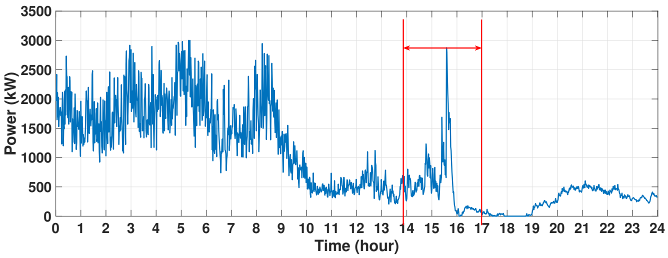
The five-phase charging demand prediction programme is deployed in the case study. Parameters are set as: a_1=15, a_2=30, a_3=45, a_4=60 and N_{max}=75. Accordingly, the maximum desired number of charging pads by demand prediction is 90, i.e. n=90.

B. WIND ENERGY

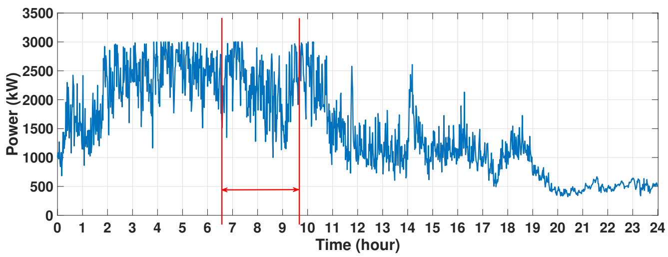
According to the maximum desired number of charging pads by demand prediction (n=90) and the nominal charging power of each pad (P_o=100 kW), the maximum charging demand became 9000 kW. Hence, three Permanent Magnet Direct Drive (PMDD 3.0MW) Wind Turbines from Goldwind Americas Inc. [47] were adopted with rated wind speed at 10.5 m/s. The dynamic power curve of the turbine is depicted in Fig. 4a. The historical observatory profiles in 2016 were obtained from Weybourne Atmospheric Observatory, University of East Anglia [48] and data of 21 March, 21 June, 21 September and 21 December were selected to represent wind conditions in spring, summer, autumn, and winter, respectively. Fig. 4b and Fig. 4c show the 24 hours wind power out in June and December.



(a) Dynamic power curve of the Gold-wind 3MW PMDD Wind Turbine



(b) 24-hour wind power out of 21 June 2016



(c) 24-hour wind power out of 18 December 2016

FIGURE 4: 24-hour wind power out of different seasons

C. NORMAL CHARGING POWER OF EACH PAD

All EVs that send charging requests will be allowed to pass the charging lane, and other EVs pass though non-charging lane. Table 2 shows the charging pad parameters. The nominal charging power of each pad was set to 100 kW, i.e. P_o=100 kW, which could provide adequate power for low-power EVs considering the efficiency of wireless power transfer. The 100 charging pads are evenly installed along the charging lane. Each pad is designed as 9 m long and the distance between two pads is 1 m. The charging lane we chose was British Motorway A1 (1 Km) as described in Section III A. Based on the actual traffic flow of the British Motorway A1, the maximum number of charging pads required is 90, as mentioned in Section III A. Under this circumstance, the maximum required number of charging pads estimated as 100. The total distance of one charging pad including the gap is 10 m. The length of the vehicle and the speed limit of British Motorway A1 is 70 mph (31m/s). Therefore, 9 m charging pads with a 1 m gap for the minimum charging time of 0.3 s is chosen in order to guarantee the sufficient charging time. However, a trade-off between power transfer efficiency

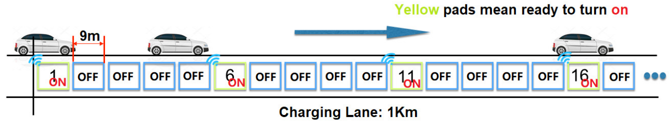


FIGURE 5: The Structure of EV Charging on Charging lane

and economy is made in the design of the actual charging pad. Power transfer efficiency of dynamic wireless EV charging can be increased by improving the coupling coefficient of a single pick-up or maximizing the number of pick-ups [49]. If the number of charging pads is maximized, the cost of the charging pad will increase consequently. So the size of charging pads in this design can be changed, depending on the actual completion and economy. Once the final number of pads to be turned on is obtained, i.e. M_r or M, the specified working pads will also be determined on an even manner:

$$s_1 = 1 \tag{16}$$

$$s_2 = s_1 + \frac{100}{\lceil M_r or M \rceil} \tag{17}$$

$$s_3 = s_2 + \frac{100}{\lceil M_r or M \rceil} \tag{18}$$

$$\cdots \tag{19}$$

$$s_{M_r[orM]} = s_{M_r-1[orM-1]} + \frac{100}{\lceil M_r or M \rceil} \tag{20}$$

In traditional charging lane design, the charging pad all turn-on, and turn-off when the EVs pass the charging pad. However, selecting the specified charging pads to switch on is the switching method in this system. Where S is the serial number (position number) of pad which needs to be switched on. Each EV in the traffic flow is charged from one specific charging pad. e.g, if 20 pads are required to be turned on, the system will automatically calculate the serial number of them: 1, 6, 11, 16, 21, 26, 31, 36, 41, 46, 51, 56, 61, 66, 71, 76, 81, 86, 91, 96, as shown in FIGURE 5.

Then the sensors at both ends of charging pads and the EV will be activated. The specified pads will be automatically turned on when EV approaching the sensing range. At the same time, the speed reduction signal will be sent to the EV driver in order to receive high charging energy within the charging time. However, the speed of the EV passing through the open charging pad is different since one charging pad can only charge one EV in sequence (one after the other). If there is high traffic flow (or many EVs that require charging), the number of charging pads that are switched on will increase. In this case, the speed of EVs is slow. EVs can get long charging time thus get the adequate charge, due to one charging pad only charge one EV. If there is free flow (or a few EVs that require charging), the number of charging pads that are switched on will decrease, as example in FIGURE. 5. In this case, the speed reduction signal is necessary when the EV approaches them to be turned on charging pad which to make sure the EVs get enough charging time. The exact

TABLE 2: Charging Pad Parameters

Charging lane length	1 km
Charging pad length	9 m
Distance between pads	1 m
Number of pads installed on the charging lane	100
Nominal power per pad	100 kw

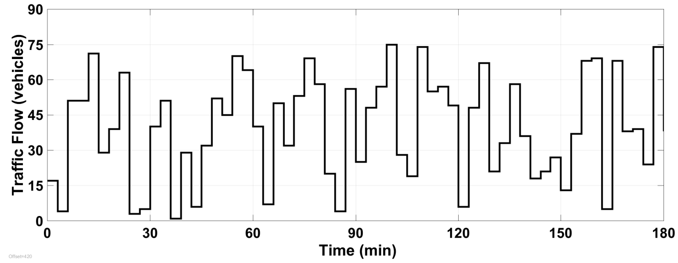
speed of EV is difficult to estimate because the amount of opening charging pads are uncertain depending on the traffic flow and wind power. In future work, the present system will be improved with a detailed algorithm to define the EV speed during this time period. After that, the pad will be automatically turned off when the EV is out of the sensing range. The EV driver will receive normal speed signal which means they could drive at any speed within the official speed limits.

IV. SIMULINK AND RESULT

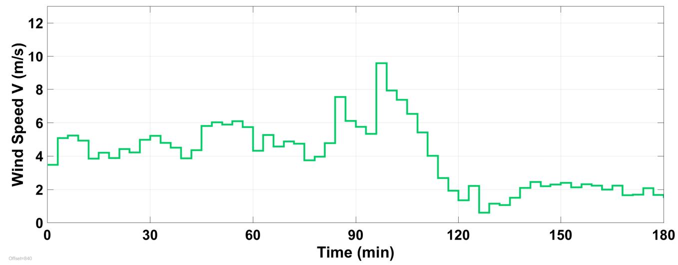
MATLAB R2016b/Simulink model was developed as shown in Fig. 8 to represent a V2G system, and used to verify the proposed algorithm for coordinating EVs charging with varying wind power and daily load. Simulation results in Fig. 6 and Fig. 7 show that the proposed charging method can effectively reduce the peak load, thereby effectively stabilise and improve the utilisation of renewable energy. The results also show the relationship between wind power, power grid, and electric vehicles charging demand. The summer weekday scenario with wind profile from 2 pm to 5 pm on 21st June 2016 with the weekday traffic flow condition was selected as an example to illustrate the performance of the proposed system.

It can be seen from Fig. 6 that although both wind speed and traffic flow very intermittently, the system reacts adaptively to the variation of these two inputs. The system can adaptively realise demand response according to customers' welfare analysis and charging price, thereby to determine the mode of power supply. Taking the consecutive interval from 120 minutes to 180 minutes as an example. During this time, the wind power is too very low to provide all charging required. The demand response is still very high, which means that the customer accepts the high price at this time. Therefore, the grid will provide energy for EVs. Taking the consecutive intervals from 57 minutes to 60 minutes as an example, the wind speed is 5.74 m/s so that about 2,600 kW wind power is generated by three turbines and 25 charging pads (M) can be supplied. However, at this time, the traffic flow reaches 64 vehicles requiring 90 charging pads (M_p) according to the five-phase charging demand prediction programme. Since $1 < M < M_p$, the system automatically publishes the price P_2 to all customers, and after demand side response programme, only 25 charging pads M_r are required, which means that only 25 customers can accept this price. Because wind energy can meet all demand required, the energy from the grid is zero.

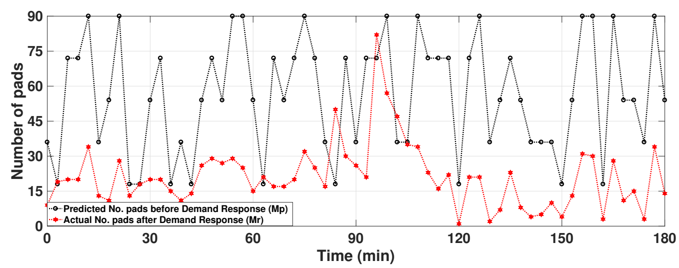
It is also noted that in Fig. 6 the five-phase charging demand prediction programme can reduce the variation of charging demand that is caused by the dynamic nature of traffic flow. In addition, the prioritised use of wind energy supply helps to mitigate the impacts of intermittency in renewable energy as well as reduce the electricity demand on the power grid. With total consumption of 15.7 MWh within three hours, only 5 MWh electricity is supplied by the power grid. More than 10 MWh electricity is saved by integrating renewable wind energy. Using the method in [50], we can find that 6.5 tons CO2 can be reduced within three hours. In other words, the overall carbon emissions could be reduced



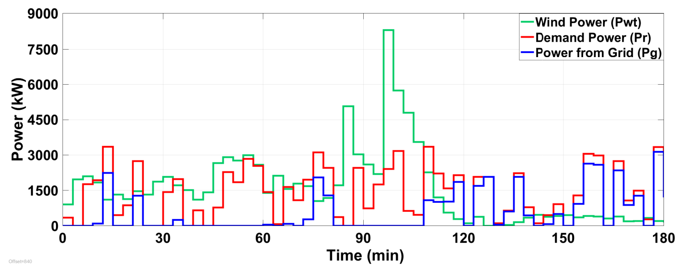
(a) Traffic flow in weekday



(b) Wind Speed

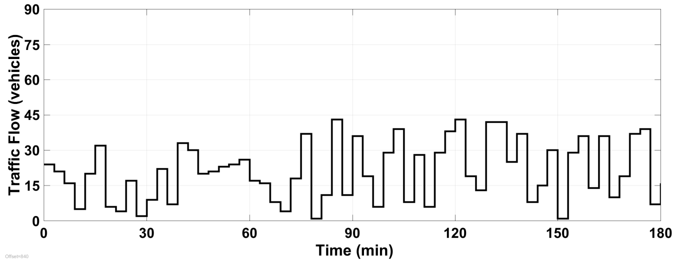


(c) The results of charging pad number

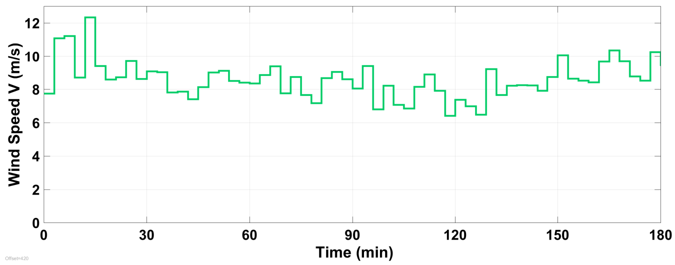


(d) The results of power

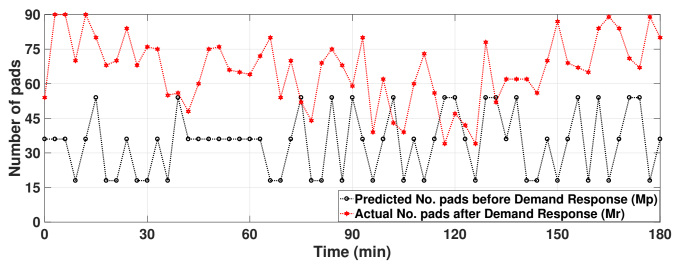
FIGURE 6: The results of system on 21st June 2016



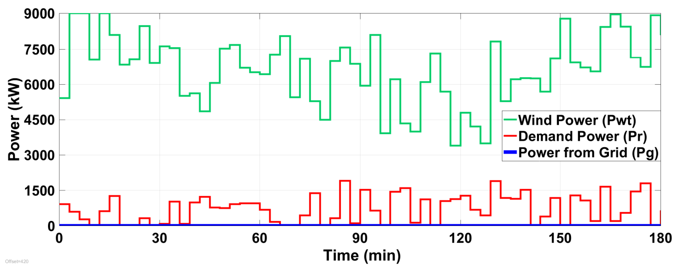
(a) traffic flow in weekend



(b) Wind Speed



(c) The results of charging pad number



(d) The results of power

FIGURE 7: The results of system on 18th December 2016

by 63.7%.

Fig. 7 shows the simulation result of winter weekend scenario with wind profile from 7:00 am to 10:00 am on 18th December 2016. The traffic flow is relaxed at the weekend, and the maximum traffic flow reaches 45 vehicles per hour. Meanwhile, the average wind speed reaches 8 m/s, and the average wind power output is 6,000 kW. The number of needed pads is much less than the number of pads that can be powered by wind energy. With the demand response module, the proposed system publishes a lower price to the customers for encouraging EVs charging. Hence, in Fig. 7c we can see that the number of pads after demand response (M_r) is more than the number of pads without demand response (M_p). The imported power from the power grid is zero, and all wind energy is used for powering EVs. This could help maximise the utilisation of renewable wind energy, reduce the additional cost for purchasing electricity from the power grid, and mitigate the intermittent impact of renewable energy to the power grid.

V. CONCLUSION

Electrification of transport is an effective approach to alleviating the impact of the energy crisis and climate change. Dynamic wireless charging is a promising way of addressing the driving range anxiety of EV users but its dynamic nature of fast-changing charging demand and strict operation requirements may pose great pressure on the power grid. An adaptive dynamic EVs wireless charging system has been presented in this paper that could best integrate renewable wind energy. Demand response programs of changing price signals between customers and operators are investigated, in order to promote the use of renewable energy, minimize the system cost, and maximize customers' benefits. The selected charging pad design not only ensures long charging time, but also enables the consumer to have a normal driving speed. The simulation results show that if the wind energy meets all charging requirements, the output power from the grid is zero; when the wind energy cannot meet all the charging requirements, the grid can supply power, and the given algorithm can reduce the demand at this time. The prioritised use of wind energy supply has helped reduce the EV charging demand on the power grid, as well as reduced carbon emissions.

Future work will include the optimal configuration of the charging pads to improve power transfer efficiency. We will improve our system and provide the algorithms to define the exact speed when the EVs pass the charging pads. Additionally, experimental tests will be performed to examine the commercial feasibility of this system in practice. The output power pulsation is one big challenge in dynamic wireless charging. In our future work, we will focus on the charging pads design and circuit topology design to solve out power pulsation problem.

APPENDIX. THE MATLAB/SIMULINK MODEL

A. THE SYSTEM MODEL

FIGURE.8A show the whole system MATLAB/Simulink Model, which includes Wind Energy Prediction Module, Charging Demand Prediction Program Module, Demand Response Module, and Automatic Selection Module. We can get the values of Wind Power (P_{wt}), Demand Power (P_r), and Power from Grid (P_g) from this model.

B. DEMAND PREDICTION PROGRAM SUBSYSTEM

FIGURE.8B show the flowchart of Charging Demand Prediction Program Subsystem. This model is aim to decide the

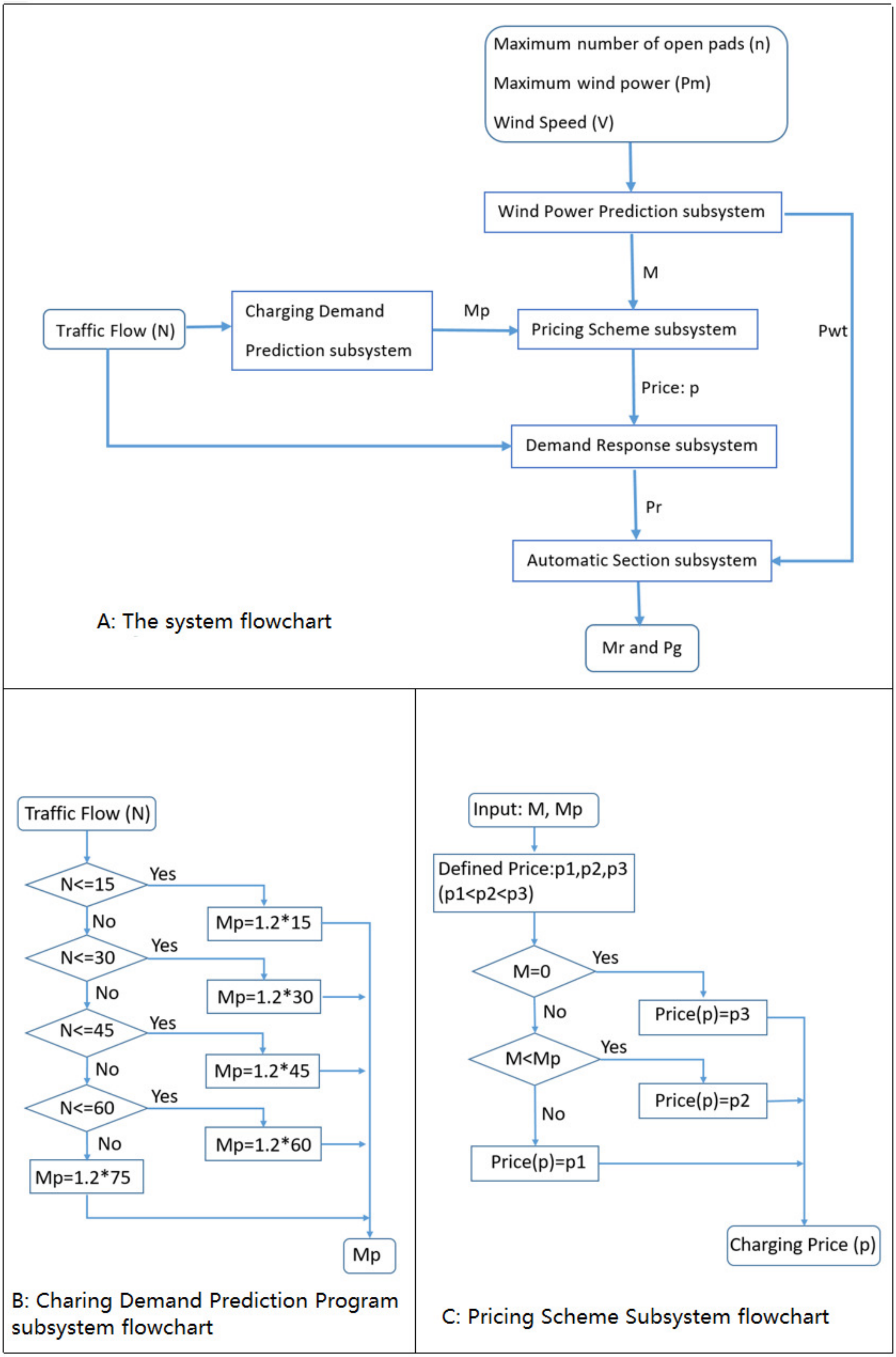


FIGURE 8: The System Model

desired number of pads (M_p) according to the traffic phase classification.

C. PRICING SCHEME SUBSYSTEM

FIGURE.8C show the flowchart of Charging Price Scheme Subsystem. This model is aim to decide the charging price p based on the values of M and M_p.

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DR. XIAOLIN MOU (S'16–M'18) received the BEng (Hons) degree in electronics engineering from Anglia Ruskin University (U.K.) in 2012 and the MSc degree in satellite communication from University of Sussex (U.K.) in 2013. In 2017, She received her Ph.D. degree in electronics engineering from Durham University (U.K.), and currently working as a Postdoctoral Research Associate within the EMD group at the University of Sheffield (U.K.).

Her research interests include wireless power transfer (WPT) technology for electric vehicle (EV) charging, particularly coil design in magnetic resonant coupling WPT, and dynamic wireless EV charging through renewable energy. Vehicle to vehicle (V2V) wireless charging, hardware design, control system and energy storage.

YINGJI ZHANG was born in Taicang, Jiangsu Province, China in 1990. She received the B.S. degree in environmental engineering and M.S. degree in naval architecture and ocean engineering from Shanghai Maritime University, Shanghai, China, in 2012 and 2014 respectively, and the M.S. degree in new and renewable energy from Durham University, Durham, UK, in 2017.

Since 2017, she has been a Bilingual Teacher teaching IELTS and science subjects in Taicang Longre Education, Taicang, Jiangsu Province, China. Her research interests includes integration of wireless charging of vehicles with renewable power sources, cultivation of Spirulina as a new biofuel feedstock in sea water and fundamental research of inactivation of microorganisms in ballast water by pulsed electric field.

DR. JING JIANG (S'10-M'12) received the Ph.D. degree in Electronic and Electrical Engineering from the University of Edinburgh, U.K. Since September 2018, she has been a Senior Lecturer in the University of Northumbria, U.K. From 2011 to 2018, she was a Research Fellow with the Centre for Communication Systems Research, University of Surrey, and then a Research Associate with the Department of Engineering, Durham University, U.K. Her current research interests include Smart Grid, Next Generation Wireless Communications, Massive MIMO, Cyber Security, Cognitive Radio Networks, Wireless Sensor Networks, and Internet of Things in Smart Energy Applications. She is on the Editorial Board of the IET Smart Grid Journal, and EURASIP Journal on Wireless Communications and Networking.

DR. HONGJIAN SUN (S'07-M'11-SM'15) received the Ph.D. degree in Electronic and Electrical Engineering from the University of Edinburgh, U.K., in 2011. He held post-doctoral positions with King's College London, U.K., and Princeton University, USA. Since 2013, he has been with the University of Durham, U.K., as a Reader in Smart Grid (with a Lecturer position in 2013-2017). He has authored or co-authored over 100 papers in refereed journals and international conferences. He has made contributions to and co-authored the IEEE 1900.6a-2014 Standard. He has authored or co-authored five book chapters, and edited two books: IET book Smarter Energy: From Smart Metering to the Smart Grid, and CRC Book From Internet of Things to Smart Cities: Enabling Technologies. His research mainly focuses on: 1) smart grid: communications and networking; 2) smart grid: demand side management and demand response; and 3) smart grid: renewable energy sources integration.